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# *Artificial Intelligence and Big Data for Dynamic Pricing in Renewable Energy Markets: A Review of Forecasting and Optimization Approaches*

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**Abstract.** The use of artificial intelligence (AI) and big data technologies has increased the usage of dynamic pricing mechanisms in renewable energy markets. The increasing amount of renewable energy being installed into the electric grid i.e. solar and wind is causing variable amounts of electricity to be produced, which is causing price volatility in the wholesale electricity market. AI-based forecasting and optimization techniques can effectively utilize large energy datasets to improve pricing methodologies.

This paper provides an overview of current research on the applications of artificial intelligence and big data for dynamic pricing in renewable energy markets. The review will discuss machine learning (ML), deep learning (DL), and reinforcement learning (RL) techniques, as well as big data platforms that are being used to process information obtained from smart meters, weather stations, and wholesale electricity market prices. Research demonstrates that AI models outperform traditional methods for forecasting; specifically, hybrid deep learning frameworks have provided very good results with mean absolute errors (MAEs) of as low as 0.138, root mean square error (RMSEs) of as low as 0.166 for various electricity markets. A comparison of CNN-BiLSTM models using hyperparameter optimization to traditional approaches resulted in an average reduction in RMSE of 16.7%, and an average reduction in MAE of 23.46%. In addition to achieving high levels of accuracy, deep learning-based forecasting tools also provide significant computational advantages. Specifically, deep learning-based forecasting tools run at least five times faster than traditional benchmarks for multiple markets. These results clearly indicate that AI-based forecasting models produce superior results relative to traditional forecasting methods as measured by metrics such as mean absolute percentage error (MAPE) and root mean square error (RMSE). Finally, this review identifies several critical challenges facing the use of AI-driven dynamic pricing in smart grid systems. These challenges include, but are not limited to, data availability, model interpretability, and regulatory constraints.

## 1 Introduction

The widespread transition to renewable-based electricity systems will radically alter the structure and function of today's electricity markets. The inherently volatile and weather-sensitive characteristics of renewable sources of energy (such as solar and wind) are producing unprecedented levels of volatility and uncertainty in the supply and price of electricity [1–5]. Previous studies have highlighted that accurate electricity price

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forecasting is essential for efficient market operation and demand response management in renewable-dominated power systems [2–5]. As a result of this increased volatility, existing static pricing methodologies are no longer sufficient; there is an immediate need for advanced, dynamic pricing methodologies that can provide incentives for efficiency in consumption while maintaining the stability of the grid [6–11].

At the same time, the increasing digitization of the electric system through the installation of smart meters, sensors and digital marketplaces has created enormous amounts of "Big Data." When combined with the exponential growth of artificial intelligence (AI) capabilities and machine learning (ML), deep learning (DL), and reinforcement learning (RL) techniques, the potential for developing advanced methods of analyzing this data for price forecasting and real-time decision making is tremendous [1, 8, 9]. As a result, researchers are actively investigating the development of the next-generation of intelligent, data-driven pricing systems that utilize the converging technologies of big data analytics and AI to advance dynamic pricing models for renewable dominated electricity markets [10, 12].

There is currently a large body of literature that explores the application of various forms of AI to pricing and forecasting tasks [2–5, 7], however, prior reviews of this literature have generally been limited to a narrow focus on forecasting methodologies [1, 2] or to more general uses of AI in the energy sector [9]. A critical gap therefore remains in terms of a comprehensive review of the literature that addresses how the combined use of AI and big data is advancing dynamic pricing models in the unique context of renewable based electricity markets. To synthesize the current state of the art and to create a common framework for evaluating the architectures and performances of proposed systems as well as identifying consistent issues and problems (e.g., scalability, interpretability, regulatory requirements) that remain to be addressed by future research efforts is essential.

To address the existing knowledge gap identified above, this study will carry out a review of the literature related to applications of AI and Big Data to support the implementation of dynamic pricing in renewable energy markets. The ultimate objectives of this review are to: (1) categorize and compare the most prominent AI-based systems and architectures for use with the relevant data; (2) synthesize the results reported from each study in terms of how well they performed and what their design was; (3) assess and criticize the major technical and non-technical hurdles to using these techniques in practice; and (4) to identify and outline needed areas of research to assist in developing and implementing new technologies to support the sustainable development and operation of intelligent energy markets. In the remainder of this paper, we will detail the subsequent steps based on our defined framework. In Section 2, we will provide a general overview of the background information needed. In Section 3, we will explain the approach to conducting our literature review. In Section 4, we will report on the summary of our analysis of the methodologies and findings. In Section 5, we will outline the technical and non-technical obstacles and limitations to employing these methods in practice. In Section 6, we will outline potential areas of future research. In Section 7, we will provide a comprehensive summary of our efforts.

## 2 Background and Key Concepts

### 2.1 Renewable Energy Markets

Modern electric power markets have a growing proportion of variable renewable generation as an outcome of an increase in the use of intermittent energy producers such as wind and solar power. The amount of electricity generated from these renewable resources is very dependent upon the weather, therefore introducing substantial amounts of uncertainty (unpredictability) and variability (intermittence) into the electric power supply [1, 5] This basic nature of renewable resources has a direct impact on how markets operate, prices form and ultimately grid reliability. Markets with a large share of renewable energy will experience greater price fluctuations and more often than not negative price events and higher demands for flexibility on both the supply and demand side of the electric system [5]. Although the emerging designs of markets (i.e. day ahead, intra-day and balancing markets) offer potential solutions, most of the current pricing mechanisms do not account for real time operating conditions of the electric system nor do they effectively encourage consumers and producers to optimize their respective consumption and production patterns [11]. Therefore, there is a critical need for advanced, data-driven pricing models to facilitate managing the natural variability and uncertainty associated with renewable energy markets [6, 11].

### 2.2 Dynamic Pricing Mechanisms

The tariffs of Dynamic Pricing are influenced by real-time variations of the price of electricity, due to the dynamics of supply, demand and restrictions on the grid. These tariffs can be implemented using different models such as TOU (Time Of Use), RTP (Real-Time Pricing) and CPP (Critical Peak Pricing). Their main purpose is to influence consumer's behavior (to move their use from peak hours to off-peak hours, or to reduce their global consumption in case of peak hours or when there is lack of supply/demand) [6]. The large-scale installation of Smart Meters and advanced telecommunications infrastructures have allowed the technical implementation of Dynamic Pricing tariffs; however, developing the best dynamic pricing strategy is still a complex problem because it includes forecasting and reacting to many nonlinear and probabilistic variables present in the energy markets [3, 4]. For this reason, Dynamic pricing mechanisms require accurate forecasting models and real-time decision-making capabilities, if we have the ability to make decisions based on real-time information and if we can optimize continuously the price of electricity, all of which represent great opportunities for the application of AI [6, 12].

### 2.3 *Artificial Intelligence and Big Data in Energy Systems*

The modern electricity grid produces an ever-growing amount of data from many different types of data sources, for example, weather monitoring stations, energy market platforms, wind farms and other forms of renewable energy generators and smart energy meters. This presents a considerable problem in terms of managing it and realizing value from it in that it contains so much information, and the rate at which it can be generated and processed is very high, and it takes on a multitude of formats [10, 13]. Cloud computing, edge computing, distributed databases are just a few examples of technology which enables the building of scalable systems to manage the large volumes of data. At the same time, artificial intelligence (AI) which includes machine learning (ML), deep learning (DL), and reinforcement learning (RL) have shown impressive capabilities to model complex system behavior, to identify non-linear relationships between variables and to learn how to behave under changing conditions [8, 9]. With regards to dynamic pricing, AI is being used to build predictive models to forecast prices [1–5, 7] to determine optimal pricing strategies [6, 11] and to provide the capability for real-time, automatic decision making [13]. The integration of AI with big data analytics provides the potential for creating smart, adaptive and cost-effective pricing systems for renewable energy markets of the future [10, 12].

## 3 Review Methodology

The review process provided an opportunity for a consistent, reproducible, and transparent examination of all available literature. Literature searches were completed in various academic databases, including ScienceDirect, SpringerLink and Scopus. All of these databases provide access to many of the top journals in the field of interest; thus, they were searched to ensure that high impact journals were included. The focus of the search was on the latest and most influential studies about the topics of artificial intelligence, big data analytics, dynamic pricing, and renewable energy markets, with a primary emphasis on studies which have been published since 2020. Therefore, the purpose of the search was to identify the most recent methodologies and technologies currently being employed in the area of interest. A combination of keywords ("dynamic pricing," "electricity price forecasting," "renewable energy markets," "machine learning," "deep learning," and "big data analytics") and Boolean operators were used to isolate relevant studies. Additionally, only peer-reviewed articles from academic journals were included in this study so as to ensure their scientific validity and relevance.
In order to organize the studies selected for inclusion based upon the AI and big data techniques they employed, the data sources utilized by those studies, the architectures of systems described in the studies, the goals of applications described in the studies, and the performance evaluation metrics used in the studies, a classification framework was developed. In addition to identifying the predominant trends and concerns within the field, and areas where additional research may be warranted, an organized and systematic review of each study enabled the identification of the most significant findings from the structured review.

## 4 AI and Big Data Techniques for Dynamic Pricing

The systematic evaluation of research on renewable energy markets and how they relate to dynamic pricing challenges has resulted in a clear categorization of types of solutions being used to address the challenges in renewable energy markets. There are three main categories of AI based methodologies that support the architecture necessary for large-scale big data systems; Machine Learning (ML), Deep Learning (DL) and Reinforcement Learning (RL). Fig. 1 illustrates the overall architecture of an AI-based dynamic pricing system, and Table 1 presents an integrated view of the types of methodologies, their uses and the references included in this study.

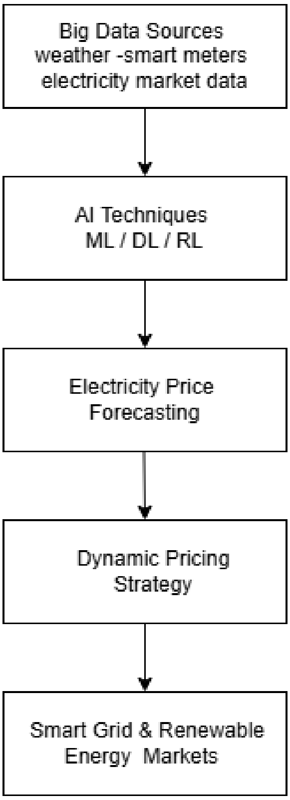


**Fig. 1.** AI-Based Dynamic Pricing Framework

**Table 1.** AI and Big Data Techniques Applied to Dynamic Pricing in Renewable Energy Markets.

| Technique | Main Purpose | Example Models | Example References |
|---|---|---|---|
| Machine Learning | Electricity price forecasting and pattern recognition | SVM, Random Forest, Gradient Boosting | [2], [8] |
| Deep Learning | Modeling temporal and nonlinear price patterns | LSTM, CNN, CNN-BiLSTM | [3], [4], [5] |
| Reinforcement Learning | Adaptive pricing and demand response optimization | Q-learning, DQN | [6], [13] |
| Big Data Platforms | Large-scale data processing and analytics | Apache Spark, Cloud computing | [10], [12] |
| Hybrid AI Systems | Integrated forecasting and optimization frameworks | DL + RL hybrid models | [3], [11] |

The primary application of machine learning algorithms is for price forecasting and pattern recognition. Deep learning algorithms can be used to identify complex nonlinear patterns within large time series data sets. There is an increasing use of reinforcement learning to optimize adaptive pricing and demand response systems.

### 4.1 Machine Learning for Forecasting and Pattern Recognition

Traditional and advanced machine learning (ML) techniques continue to be at the core of the process of forecasting electricity prices, which is an essential input to all pricing models. Support Vector Machines (SVM) and Random Forest algorithms, among other ensemble methods, are well regarded for their capacity to model nonlinear relationships in the marketplace that involve the output of renewable generators and trends in customer demand [2, 8], and these models can serve as a baseline for comparison to other approaches or can be used within more complex modeling processes. Broader reviews support the use of ml as a flexible and effective technology across many different types of applications within the energy systems area [9].

### 4.2 The Rise of Deep Learning Models

Deep learning (DL) models have shown greater performance capabilities than others especially when it comes to identifying complex patterns of temporal dependency and processing large dimensional datasets that characterize contemporary energy market data. LSTM networks as well as CNNs are being utilized for time series forecasts [1]. These forecasting models learn a complex mapping function from input features to predicted electricity prices, which can be mathematically represented as:

$$\hat{P}_t = f(X_t, \theta) \qquad (1)$$

Where $\hat{P}_t$ is the predicted electricity price at time t, $X_t$ is the vector of input features (including historical prices, weather data, demand patterns, and renewable generation forecasts), and θ represents the model parameters learned during training.

Hybrid or ensemble DL models that use a combination of different architectures are currently trending to provide increased accuracy and robustness. Studies have been successful in implementing CNN-BiLSTM models with hyperparameters optimized [4], as well as other hybrid frameworks using multiple data sources and/or additional algorithmic steps to forecast day ahead prices [3, 5, 7]. In addition to showing measurable improvement in error metrics (RMSE, MAE) etc, these models also demonstrate a higher level of performance compared to their respective traditional machine learning (ML) benchmarks.

### 4.3 Reinforcement Learning for Adaptive Strategy Optimization

Although ML & DL are used for forecasting, RL can be used for direct strategy optimization in the context of optimizing price and/or DR policy. By using a simulated or live marketplace environment as its learning environment, an agent learns what the optimal pricing and/or DR policy should be through continuous interaction with the environment; this makes it well-suited for use in real-time and adaptive pricing applications. Some examples of how this could be applied include: developing incentive-based demand response strategies for smart-grids [6], and developing real-time bid and price management strategies for load aggregators [13]. In both examples, RL has demonstrated significant promise for enabling dynamic, closed loop pricing/DR strategies that adapt based on changing conditions in the grid.

### 4.4 *The Enabling Role of Big Data Architectures*

The ability to effectively apply these described AI models will depend on the availability of scalable big data architectures to process the data coming from smart meters, weather sensors, and markets at a rate of volume, velocity, and variety. Research has shown how big data processing systems such as Apache Spark have been used in large scale load forecasting and demand response studies; they also provide examples of successful project implementations (e.g., Low Carbon London) [10]. Additionally, the emergence of platforms that integrate both big data management and AI analytics is providing the necessary support to the new generation of electric utilities and their associated technologies to create an end-to-end pipeline from collecting data to deploying models [12].

### 4.5 *Convergence: Hybrid and Market-Aware Systems*

The main trend is toward a complete system combining forecast, optimization, and learning parts using integrated solutions. This trend can be seen both from a technical standpoint as hybrid AI models that use DL forecasting with RL optimization [6, 13] and structural standpoint through AI based on market frameworks that introduce new mechanisms for peer-to-peer energy trading and dynamic pricing within regulatory boundaries [11]. Both are at the front of the research, and they aim to create an entire (holistic), large scale, and market aware smart pricing systems.

**Table 2.** Comparison of Recent AI-Based Electricity Price Forecasting Studies.

| Study | Method | Dataset | Main Contribution |
|---|---|---|---|
| Lago et al. (2021) | Machine learning ensemble | European markets | Benchmark framework for forecasting |
| Huang et al. (2024) | Hybrid deep learning | Chinese electricity market | Improved day-ahead price prediction |
| Mubarak et al. (2024) | CNN-BiLSTM | Smart grid datasets | Hybrid DL forecasting |
| Aliyon & Ritvanen (2024) | Deep learning | European electricity markets | Analysis of price predictability |
| Salazar et al. (2023) | Reinforcement learning | Smart grid demand response | Adaptive pricing strategy |

Table 2 presents a comparison of representative studies that apply artificial intelligence techniques to electricity price forecasting and dynamic pricing. The table highlights the diversity of datasets, modeling approaches, and research objectives addressed in recent literature.

# 5 Challenges and Limitations

Although both AI and Big Data have shown promise in making dynamic pricing in renewable energy more efficient, there are a number of key barriers that prevent them from being implemented in practice. The first barrier to implementing these technologies has been related to data - namely how to collect, store, process and analyze high-quality data in real time in a way that aggregates large amounts of disparate data types (e.g., market price, weather conditions, customer behaviors) to provide reliable output from models [10]. This data-related challenge is compounded by a second major challenge associated with the interpretability/explainability of the models. While advanced AI models, especially those using deep learning and/or reinforcement learning, can be highly accurate in their predictions and actions, they typically operate as "black boxes" (i.e., the inputs/outputs, internal workings and decision-making processes are unknown), thereby generating skepticism/trust issues among regulators, market participants and customers and hindering acceptance of new models/systems [1, 4, 6, 11]. In addition to technical challenges, there are also regulatory and market design barriers to implementation. Current frameworks for setting prices, participating in markets and handling data privacy are generally incompatible with the rapid development and data-intensive nature of AI-based pricing systems, a mismatch that is not typically examined in detail in technical analyses [11]. Last, the question of whether scalable, broadly applicable models exist remains an open one. Many models have been validated in case studies/simulations but lack evidence that they will perform well in other grid environments/market regimes [10, 12]. Therefore, overcoming these interconnected technical, regulatory and practical challenges is necessary for advancing from research into trusted, commercially viable intelligent pricing systems.

# 6 Research Gaps and Future Directions

This study has identified several key research areas where further work is needed to progress the area of using artificial intelligence to create dynamically priced renewable energy systems. One of the primary research areas needing focus is the creation of Explainable Artificial Intelligence (XAI) frameworks for energy economics, which will be able to provide accurate forecasts and optimize prices, while also allowing users to understand how the AI made its pricing decisions in an auditable manner, so as to build trust with all stakeholders [6, 11]. At the same time, the research community needs to develop highly scalable, adaptive system architectures to process massive amounts of rapidly changing data to produce real-time price signals; this is in addition to the current use of offline analytics to develop price signals [10, 12]. In addition, a major gap currently exists in the area of integrating regulatory and market design constraints into AI models. Future research should move from developing algorithms that exist in a regulatory vacuum, to designing the pricing mechanisms that are developed through the use of AI models to be both economically efficient, and legal by default [11]. Lastly, to confirm the applicability of theoretical advances, the field of AI-DRP for RENs requires extensive testing and real world implementation of proposed models in pilot projects or experimental market environments. The testing of these models in real world environments will allow researchers to determine whether their proposed models perform well, are robust, and have the potential to positively impact society on a large scale, ultimately closing the gap between theory and practice, and enabling the establishment of sustainable and intelligent energy markets [3, 13].

## 7 Conclusion

This review of the literature examined recent advances in artificial intelligence and big data techniques for enabling dynamic pricing in renewable energy markets. The review clearly demonstrates that hybrid and adaptable AI-based models which utilize both deep learning techniques for forecasting as well as reinforcement learning techniques for optimizing prices, and scalable big data infrastructure to execute those optimized prices, outperform traditional price-setting methodologies. Nevertheless, there exist significant barriers to achieving transformative impact with AI-based dynamic pricing models beyond mere technological sophistication. Most notably, the complexity associated with explaining how black box AI models arrive at their conclusions, the regulatory misalignment between traditional regulatory structures and modern AI-based models, and the ability to scale solutions developed within academic or research environments into real world operational environments, are all significant impediments to wide-scale adoption of such technology. Consequently, the development of truly transformative pricing models will require a comprehensive research approach which focuses upon developing both transparent and explainable algorithms as well as regulatory aware design of those models; and finally rigorous testing and validation of those models within realistic operational environments. By addressing each of these interdependent challenges, researchers and practitioners can facilitate the widespread adoption of reliable, effective and resilient pricing systems necessary for facilitating a global transition to renewable energy-based power systems.

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